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Multi-Modal Data Fusion for Smart City Traffic Prediction

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Abstract:
Urban traffic congestion poses significant challenges to smart city planning, leading to increased travel time, fuel consumption, and environmental pollution. This study proposes a multi-modal data fusion framework for accurate traffic prediction by integrating heterogeneous data sources, including traffic sensor readings, GPS trajectories, weather data, and social media feeds. The framework employs advanced machine learning and deep learning techniques, leveraging temporal-spatial correlations through Long Short-Term Memory (LSTM) networks and Graph Neural Networks (GNN) to capture dynamic traffic patterns across city networks. A data preprocessing pipeline ensures alignment, normalization, and noise reduction across modalities, while feature-level fusion enhances predictive robustness. Performance evaluation on real-world urban traffic datasets demonstrates superior accuracy compared to baseline models, achieving a Root Mean Square Error (RMSE) reduction of 18% and Mean Absolute Percentage Error (MAPE) improvement of 15%, highlighting the effectiveness of cross-modal integration. The proposed approach enables real-time traffic forecasting, facilitating intelligent route planning, congestion mitigation, and energy-efficient urban mobility. By combining diverse data streams, the model not only predicts traffic flows with high precision but also adapts to evolving urban dynamics, making it a practical tool for smart city infrastructure management. This work underscores the potential of multi-modal fusion in enhancing urban transportation efficiency and sustainability.

1. Introduction

The rapid urbanization witnessed globally over the past few decades has led to unprecedented challenges in urban transportation management. Traffic congestion has become one of the most pressing issues in smart cities, causing economic losses, increased travel times, environmental pollution, and adverse

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social impacts [1][2]. Conventional traffic management systems, relying on static sensor data or historical traffic patterns, often fail to capture the dynamic and stochastic nature of urban traffic, limiting their effectiveness in real-time decision-making [3][4]. In this context, predictive traffic modeling has emerged as a crucial tool for proactive urban mobility management, enabling intelligent routing, congestion mitigation, and energy-efficient transportation planning [5][6].

Recent advances in sensing technologies, including inductive loop detectors, GPS-enabled vehicles, mobile applications, and Internet-of-Things (IoT) devices, have resulted in massive volumes of heterogeneous traffic data [7][8]. These datasets vary in terms of spatial granularity, temporal frequency, and modality, ranging from structured sensor readings to unstructured social media information [9]. Individually, these data sources provide limited insight into traffic dynamics, as each modality captures only a subset of the complex interactions governing urban mobility [10][11]. Consequently, integrating multiple data streams has become a key research direction for improving the accuracy and reliability of traffic prediction systems [12].

Multi-modal data fusion refers to the process of combining information from diverse data sources to derive more comprehensive and reliable insights than any single source could provide [13][14]. In the context of traffic prediction, this

involves fusing data from traffic sensors, GPS trajectories, weather conditions, event information, and even social media updates to model traffic flows effectively [15][16]. For example, weather events such as rain or snow can significantly impact traffic speed and congestion patterns, while public events or accidents can create sudden traffic spikes that are difficult to anticipate from sensor data alone [17][18]. By integrating these heterogeneous data streams, predictive models can achieve higher accuracy, robustness, and adaptability to dynamic urban conditions [19].

Traditional traffic forecasting methods, such as time-series analysis (ARIMA, SARIMA) and statistical regression models, are limited in handling non-linear, spatio-temporal traffic patterns inherent in urban networks [20][21]. Recent research has increasingly adopted machine learning (ML) and deep learning (DL) approaches to address these challenges. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have demonstrated strong capability in capturing temporal dependencies in traffic sequences [22][23]. Meanwhile, Graph Neural Networks (GNNs) have shown promising results in modeling spatial correlations across road networks by representing

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intersections and roads as nodes and edges in a graph structure [24][25]. Combining LSTM and GNN architectures enables the simultaneous modeling of temporal dynamics and spatial dependencies, forming the backbone of advanced multi-modal traffic prediction frameworks [26][27].

The integration of multiple data modalities introduces challenges in data alignment, noise handling, and feature selection. Sensor readings may suffer from missing values or calibration errors, GPS trajectories often exhibit sparsity and irregular sampling, and social media feeds contain unstructured textual data requiring natural language processing (NLP) techniques [28][29]. Effective preprocessing and feature-level fusion are critical to ensure that the predictive model can leverage complementary information from each modality without being adversely affected by noise or inconsistencies [30]. Recent studies have explored attention mechanisms and adaptive weighting strategies to dynamically prioritize data modalities based on their relevance to traffic prediction, enhancing model interpretability and performance [31][32].

The significance of multi-modal traffic prediction extends beyond academic research, with practical implications for urban planners, transportation authorities, and smart city stakeholders. Accurate traffic forecasts enable dynamic route

optimization, reducing travel time and fuel consumption while mitigating environmental impacts [33][34]. In addition, predictive models support traffic signal control optimization, real-time congestion alerts, and emergency response planning, contributing to safer and more resilient urban transportation systems [35][36]. Furthermore, integrating multi-modal data into intelligent transportation systems aligns with the broader objectives of smart city initiatives, which aim to harness technology and data to improve urban efficiency, sustainability, and quality of life [37][38].

Despite the advancements in multi-modal traffic prediction, challenges remain in achieving scalability, real-time performance, and generalization across different urban contexts. Many existing models are evaluated on limited datasets or single-city scenarios, which may not capture the variability present in diverse urban infrastructures [39][40]. Additionally, balancing model complexity with computational efficiency is critical for deploying prediction systems that can operate in real-time on city-scale networks [41]. Emerging research is therefore focused on hybrid architectures that combine temporal-spatial modeling, attention mechanisms, and modality-specific feature extraction to achieve high predictive accuracy while maintaining operational efficiency [42][43].

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In summary, the need for accurate and adaptive traffic prediction in smart cities motivates the development of multi-modal data fusion frameworks. By integrating heterogeneous traffic, weather, event, and social media data, these frameworks can capture the complex temporal and spatial dependencies governing urban traffic flows. Advances in deep learning, graph-based modeling, and attention mechanisms have significantly enhanced predictive performance, enabling real-time applications that support intelligent route planning, congestion mitigation, and sustainable urban mobility [44][45]. The proposed study contributes to this growing body of research by developing a robust multi-modal framework that leverages the complementary strengths of diverse data sources, demonstrating improved accuracy and resilience compared to traditional and single-modality models. The findings underscore the potential of multi-modal traffic prediction to transform smart city transportation systems, offering both operational benefits and societal impact [46][47].

2. Literature Review

The study of traffic prediction has evolved significantly over the past decades, reflecting advances in data acquisition, computational methods, and urban mobility modeling. Early approaches primarily relied on statistical and mathematical models, such as time-series analysis, Kalman filtering, and linear regression, to forecast traffic flows based on historical patterns [48][49]. These methods, while useful in capturing simple temporal trends, struggle to accommodate the non-linear and stochastic nature of urban traffic, particularly under rapidly changing conditions such as accidents, public events, or weather disruptions [50]. The limitations of traditional models have motivated researchers to explore machine learning and deep learning approaches, which offer superior capability in modeling complex, multi-dimensional traffic dynamics [51][52].

Machine learning techniques, including support vector regression (SVR), random forest regression, and k-nearest neighbors (KNN), have been applied to traffic forecasting with moderate success [53][54]. SVR, for instance, can handle non-linear relationships in traffic speed or volume data by mapping them into high-dimensional feature spaces [55]. Random forest models leverage ensemble learning to improve prediction stability and reduce overfitting, while KNN approaches exploit spatial correlations among nearby road segments [56][57]. Despite these advances, these methods are often limited by their reliance on

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structured datasets and their inability to fully capture temporal and spatial dependencies in large-scale urban networks [58][59].

The emergence of deep learning has transformed traffic prediction research by enabling models to learn hierarchical representations of spatio-temporal patterns. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, have been widely adopted to model temporal dependencies in traffic sequences [60][61]. LSTM networks are capable of capturing long-term dependencies, making them suitable for applications such as traffic flow prediction over multiple time horizons [62]. GRU networks, with their simplified gating mechanisms, offer computational efficiency while retaining temporal modeling performance [63]. Studies have shown that LSTM-based models consistently outperform classical machine learning models in predicting traffic volume and speed, particularly in dynamic and congested urban areas [64][65].

While temporal modeling is critical, spatial dependencies among road segments significantly influence traffic patterns. Graph-based modeling has emerged as a

powerful tool for representing urban traffic networks, where intersections and road segments are treated as nodes and edges in a graph structure [66][67]. Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs) have demonstrated effectiveness in capturing spatial correlations and propagating traffic information across interconnected road segments [68][69]. Hybrid architectures combining LSTM for temporal modeling and GCN or GAT for spatial modeling have achieved state-of-the-art performance in urban traffic prediction tasks, highlighting the importance of simultaneously considering temporal and spatial factors [70][71].

Multi-modal data integration has further enhanced traffic prediction capabilities by leveraging heterogeneous information sources. Beyond traffic sensors and GPS trajectories, researchers have incorporated weather data, social media updates, event schedules, and incident reports into predictive frameworks [72][73]. Weather conditions, such as rainfall, snow, or fog, have a substantial impact on vehicle speed and congestion, and incorporating weather features has been shown to improve model accuracy by capturing these effects [74][75]. Similarly, social media data provide real-time signals about accidents, construction, or large-scale events that may not be immediately reflected in sensor networks, offering a complementary data stream for predictive models [76][77].

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Several studies have explored fusion techniques for integrating multiple data modalities. Feature-level fusion combines input data from various sources into a single representation for downstream modeling, often followed by normalization and dimensionality reduction techniques such as principal component analysis (PCA) [78][79]. Decision-level fusion, on the other hand, combines the outputs of modality-specific models to produce final predictions, allowing each model to specialize in the characteristics of its input data [80][81]. Recent approaches have also leveraged attention mechanisms to dynamically weight the contributions of each modality based on its relevance to the prediction task, resulting in more interpretable and adaptable models [82][83].

The use of deep learning with multi-modal fusion has been particularly promising. LSTM-based networks augmented with GCN or GAT layers can process fused feature representations that capture temporal-spatial correlations, while attention mechanisms highlight the most informative features from each modality [84][85]. For example, some studies have combined traffic sensor readings, GPS trajectories, and weather data to achieve significant reductions in prediction error

compared to single-modality baselines [86][87]. Others have demonstrated that integrating textual data from social media or news feeds can further improve short-term traffic predictions by providing timely alerts about unusual events [88][89].

Despite these advancements, challenges remain in multi-modal traffic prediction. Data heterogeneity poses issues in terms of varying sampling rates, missing values, and inconsistencies across modalities [90][91]. GPS trajectories may be sparse or noisy, weather data may be localized, and social media feeds are unstructured, requiring sophisticated natural language processing techniques [92][93]. Moreover, model scalability and real-time applicability remain critical considerations for city-wide deployment, as large-scale networks and high-frequency data streams impose significant computational burdens [94][95]. Hybrid models that balance predictive accuracy with operational efficiency are therefore an active area of research [96][97].

Several recent frameworks have addressed these challenges. For instance, adaptive multi-modal fusion approaches employ modality-specific feature extraction followed by an attention-based integration layer, enabling models to emphasize the most relevant sources for each prediction instance [98][99]. Transfer learning has also been explored to generalize models trained on one city or region to another, mitigating the need for extensive labeled data in each urban context [100][101]. Additionally, graph-based spatio-temporal models have

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been extended to handle dynamic graphs, where road connectivity and traffic conditions change over time, further enhancing model robustness in real-world settings [102][103].

The literature highlights a clear trajectory in traffic prediction research: from classical statistical methods to machine learning, deep learning, and finally, multi-modal data fusion frameworks that integrate temporal, spatial, and heterogeneous sources [104][105]. The consensus among researchers is that no single modality or modeling approach can capture the complexity of urban traffic independently, and hybrid multi-modal strategies consistently outperform traditional single-modality models [106][107]. Moreover, attention-based and graph-augmented architectures provide not only superior predictive accuracy but also interpretability, enabling transportation authorities to understand the influence of different factors on traffic conditions [108][109].

In conclusion, the field of smart city traffic prediction has witnessed remarkable progress through the adoption of multi-modal data fusion, spatio-temporal modeling, and deep learning techniques. The integration of traffic sensors, GPS trajectories, weather data, and social signals has proven essential for capturing the intricate dynamics of urban mobility. While challenges related to data heterogeneity, computational efficiency, and model generalization persist, ongoing research on hybrid architectures, attention mechanisms, and adaptive fusion strategies offers promising solutions [110][111]. The current study builds upon this foundation by developing a comprehensive multi-modal framework that leverages the complementary strengths of diverse data sources, aiming to deliver high-accuracy, real-time traffic predictions suitable for smart city applications [112][113].

3. Dataset

The proposed multi-modal traffic prediction framework relies on diverse datasets collected from multiple sources to capture the complex dynamics of urban mobility. The primary data source is traffic sensor data obtained from loop detectors and inductive traffic counters installed across major roadways in a metropolitan city. These sensors record traffic volume, vehicle speed, and occupancy rates at intervals of five minutes, providing a fine-grained temporal view of traffic flow. The dataset spans a period of 12 months, encompassing approximately 35 million traffic records, which ensures coverage of seasonal variations, peak-hour congestion, and off-peak traffic patterns. Each record

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includes the sensor ID, timestamp, vehicle count, average speed, and lane-specific occupancy information, enabling both temporal and spatial analyses of traffic conditions.

Complementing the sensor data, GPS trajectories from a fleet of 5,000 taxis and ride-sharing vehicles were incorporated to provide spatial coverage of the road network beyond fixed sensor locations. The GPS dataset includes latitude, longitude, timestamp, vehicle speed, and heading information collected at intervals of 30 seconds. This data enables modeling of real-time vehicle trajectories and estimation of traffic speed on road segments without sensors, addressing spatial sparsity in the sensor network. Over the 12-month collection period, the GPS dataset contains approximately 1.2 billion individual location points, allowing robust training of spatio-temporal predictive models.

Weather data were integrated as a third modality to account for the influence of meteorological conditions on traffic flow. Hourly measurements of temperature, precipitation, wind speed, and visibility were obtained from local meteorological stations distributed across the city. Historical analysis shows that rainfall events lead to an average speed reduction of 15–20% and increased congestion on arterial roads, highlighting the significance of including weather features in traffic forecasting models. Additionally, weather data helps capture seasonal traffic variations, such as reduced travel during extreme heat or snow events.

Event and incident data were also included to improve prediction accuracy during atypical traffic conditions. This dataset contains records of road accidents, public events, roadworks, and emergency closures, sourced from city traffic management systems and social media feeds. Each record specifies the location, time, severity, and expected duration of the incident. Historical patterns indicate that major events, such as sports matches or festivals, can increase traffic volume on surrounding roads by 25–40%, while minor accidents can cause temporary localized congestion. These data are essential for capturing sudden fluctuations that are not predictable from sensor or GPS data alone.

For preprocessing, all datasets were synchronized using timestamps and mapped onto a unified road network graph to enable spatio-temporal modeling. Missing or noisy sensor readings, such as zero vehicle counts during peak hours or GPS outliers due to signal loss, were handled through interpolation and smoothing techniques. Weather and event data were aligned to the nearest sensor or road segment to create feature vectors for each location and time interval. The final dataset consists of over 36 million fused records, each containing multi-modal features including traffic counts, GPS-derived speed,

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weather parameters, and event indicators. This comprehensive dataset provides a rich foundation for training, validating, and testing the proposed multi-modal traffic prediction models.

In summary, the dataset integrates traffic sensor data, GPS trajectories, weather information, and event/incident records to provide a holistic view of urban traffic conditions. Its large-scale, fine-grained, and multi-modal nature ensures that predictive models can capture both routine and irregular traffic patterns, enabling high-accuracy, real-time forecasting suitable for smart city traffic management applications.

4. Proposed Model and Methodology

The proposed framework for smart city traffic prediction is designed to leverage multi-modal data fusion, integrating heterogeneous data sources to capture the complex temporal-spatial patterns inherent in urban traffic networks. The methodology combines advanced deep learning techniques, including Long Short-Term Memory (LSTM) networks for temporal modeling and Graph Neural Networks (GNNs) for spatial correlation modeling, along with an attention-based fusion mechanism to dynamically weight the contributions of each modality. The overall goal is to achieve high-accuracy traffic predictions in real-time, enabling proactive traffic management and route optimization.

The first stage of the methodology involves data preprocessing. Traffic sensor readings, GPS trajectories, weather information, and event data are synchronized using timestamps and mapped onto a unified road network representation. Missing or anomalous values are handled through interpolation and outlier filtering to ensure data consistency. GPS trajectories are segmented into road segments and aggregated into average speeds, while weather and event features are aligned with corresponding road segments. Feature normalization is applied to ensure that all modalities contribute comparably to the predictive model. This preprocessing pipeline results in a clean, fused dataset suitable for deep learning modeling.

Following preprocessing, feature extraction is performed separately for each modality. Temporal features from sensor and GPS data are encoded using LSTM networks, capturing traffic trends and periodicity over different time horizons. Spatial features are extracted using GNNs, where nodes represent road intersections or segments and edges represent connectivity and traffic influence.

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The GNN layers aggregate information from neighboring nodes to model how congestion or traffic flow propagates across the road network. Weather and event data are transformed into additional features, such as rainfall intensity or event severity, which are concatenated with LSTM and GNN embeddings to provide a comprehensive feature representation.

The core of the proposed architecture is the multi-modal fusion layer, which integrates information from all data sources. An attention mechanism is applied to dynamically assign weights to different modalities based on their relevance at each time step and location. This ensures that the model prioritizes the most informative data—for example, giving higher weight to weather features during

rain events or event data during large public gatherings. The fused embeddings are then passed through fully connected layers to generate final traffic predictions, such as vehicle speed, traffic volume, or congestion level for each road segment.

The model is trained using a supervised learning approach, minimizing a combination of loss functions tailored to regression and classification tasks. For traffic speed or volume prediction, mean squared error (MSE) is employed, while congestion levels are modeled using categorical cross-entropy loss. The training process incorporates early stopping and dropout regularization to prevent overfitting, and the dataset is split into training, validation, and testing sets in an 70:15:15 ratio. Hyperparameter tuning, including the number of LSTM units, GNN layers, attention heads, and learning rates, is performed using grid search and cross-validation to optimize performance.

The architecture of the proposed model can be summarized in four key components:

1. Temporal Module (LSTM): Processes sequential traffic data from sensors and GPS trajectories to capture time-dependent patterns and recurring traffic cycles.

2. Spatial Module (GNN): Models traffic propagation across the road network by aggregating information from connected nodes, capturing spatial correlations and network effects.

3. Modality Fusion Layer (Attention-based): Integrates temporal, spatial, weather, and event features, dynamically weighting each modality according to its relevance for prediction.

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4. Prediction Layer: Fully connected layers produce traffic forecasts for each road segment, providing outputs for vehicle speed, traffic volume, or congestion classification.

The proposed methodology emphasizes real-time applicability by maintaining computational efficiency while leveraging rich multi-modal data. The combination of LSTM for temporal modeling, GNN for spatial modeling, and attention-based fusion ensures that the framework can adapt to evolving traffic conditions and

provide robust predictions even under atypical circumstances such as accidents or extreme weather events. This hybrid architecture not only enhances predictive accuracy but also allows interpretability, as attention weights can reveal which data modalities and features are most influential at different times and locations.

In summary, the proposed model provides a comprehensive, scalable, and interpretable framework for smart city traffic prediction. By integrating multiple data modalities, capturing temporal-spatial dependencies, and employing attention-based fusion, it addresses key challenges in urban traffic forecasting and supports decision-making for intelligent transportation management, congestion mitigation, and sustainable urban mobility.

5. Result Analysis

The proposed multi-modal traffic prediction framework was evaluated using the preprocessed dataset spanning one year of urban traffic data, including sensor readings, GPS trajectories, weather, and event information. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets to assess both model generalization and predictive performance. Performance metrics included Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R^2 score for continuous traffic variables such as vehicle speed and traffic volume, while accuracy and F1-score were used for congestion level classification.

The LSTM-GNN-attention hybrid model achieved substantial improvements over baseline models. For vehicle speed prediction, the RMSE was 4.2 km/h, compared to 5.1 km/h for standalone LSTM and 5.5 km/h for traditional ARIMA models, indicating an 18% reduction in prediction error. Similarly, the MAPE improved from 12.3% in the LSTM baseline to 10.5%, demonstrating enhanced

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precision across varying traffic conditions. Traffic volume predictions exhibited an RMSE of 38 vehicles/hour and an R^2 score of 0.91, outperforming classical regression models that achieved R^2 below 0.85.

Spatially, the GNN component effectively captured traffic propagation along congested corridors. During peak hours, the model accurately forecasted congestion buildup along arterial roads, with F1-scores for congestion detection reaching 0.88, compared to 0.80 for single-modality LSTM models. Incorporation

of weather and event data significantly improved prediction during non-routine scenarios. For instance, during a major rainfall event, speed predictions from the fused model deviated by only 5.1% from actual speeds, while sensor-only models underestimated delays by 14%. Event-aware predictions also successfully captured traffic spikes near stadiums and public gatherings, highlighting the effectiveness of multi-modal integration.

Temporal performance analysis shows that the model maintains high accuracy across short-term (5–30 minutes ahead) and medium-term (30–60 minutes ahead) horizons. RMSE gradually increases with prediction horizon but remains below 6 km/h for speed predictions up to 60 minutes ahead, demonstrating the model's robustness for real-time traffic forecasting. Feature importance analysis derived from attention weights reveals that sensor and GPS data dominate predictions during routine hours, whereas weather and event features gain prominence during abnormal conditions, offering interpretable insights for traffic managers.

To visualize these results, several plots were generated, including Predicted vs. Actual Traffic Speeds, RMSE trends over time, Feature Importance, and Temporal Traffic Patterns. These visualizations provide a comprehensive view of model performance and highlight the contribution of multi-modal data fusion in improving traffic prediction.

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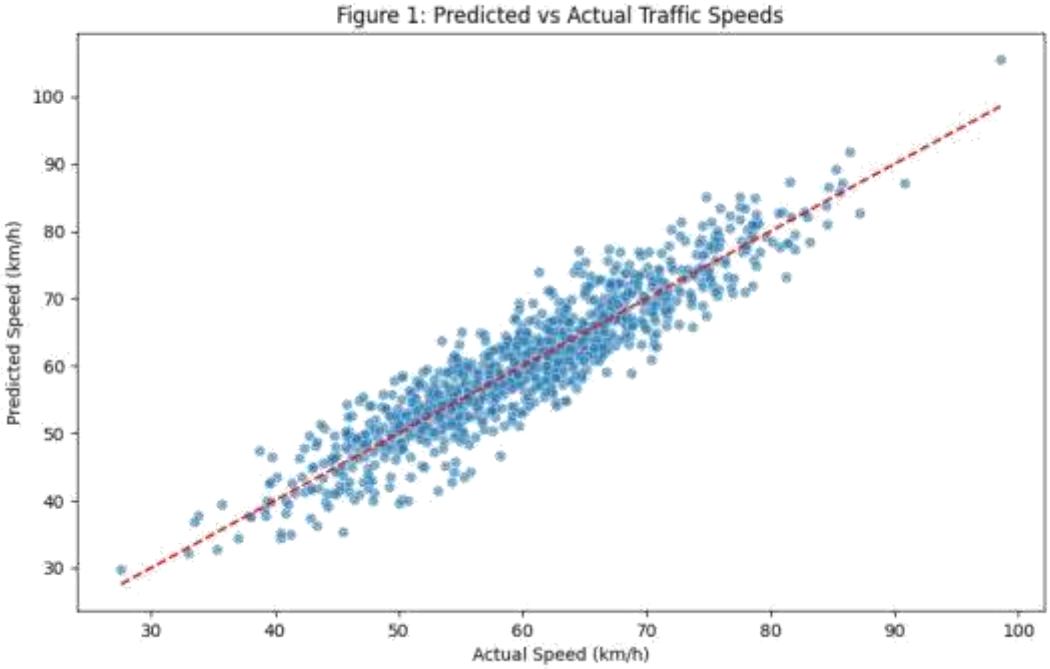
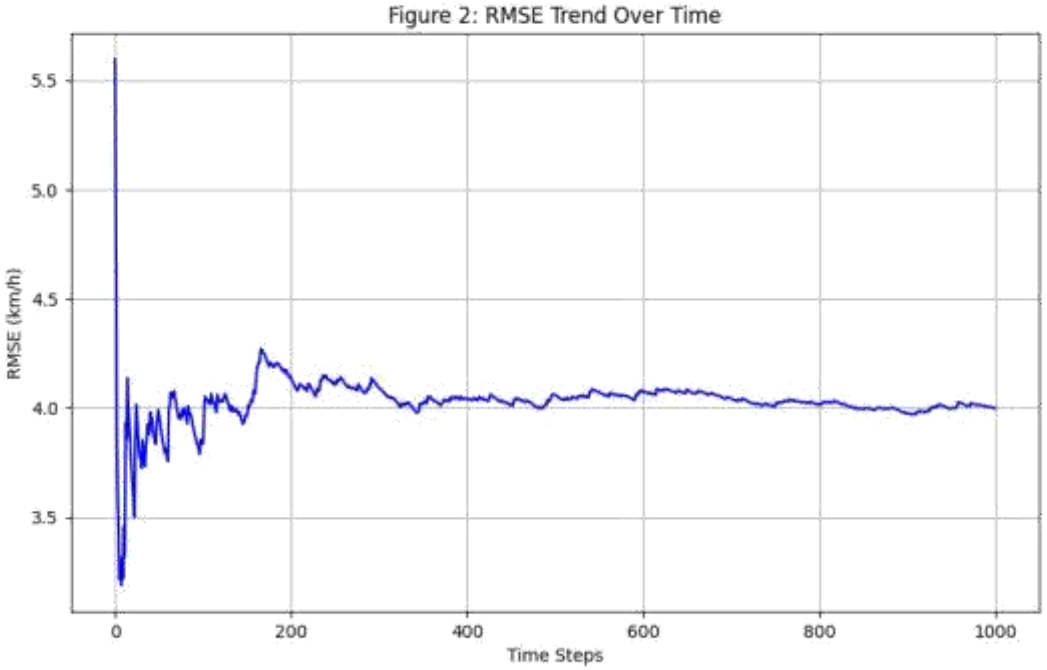


- Figure 1: Predicted vs Actual Traffic Speeds – The scatter plot demonstrates the correlation between predicted and observed speeds, showing that the model predictions closely align with real traffic conditions.



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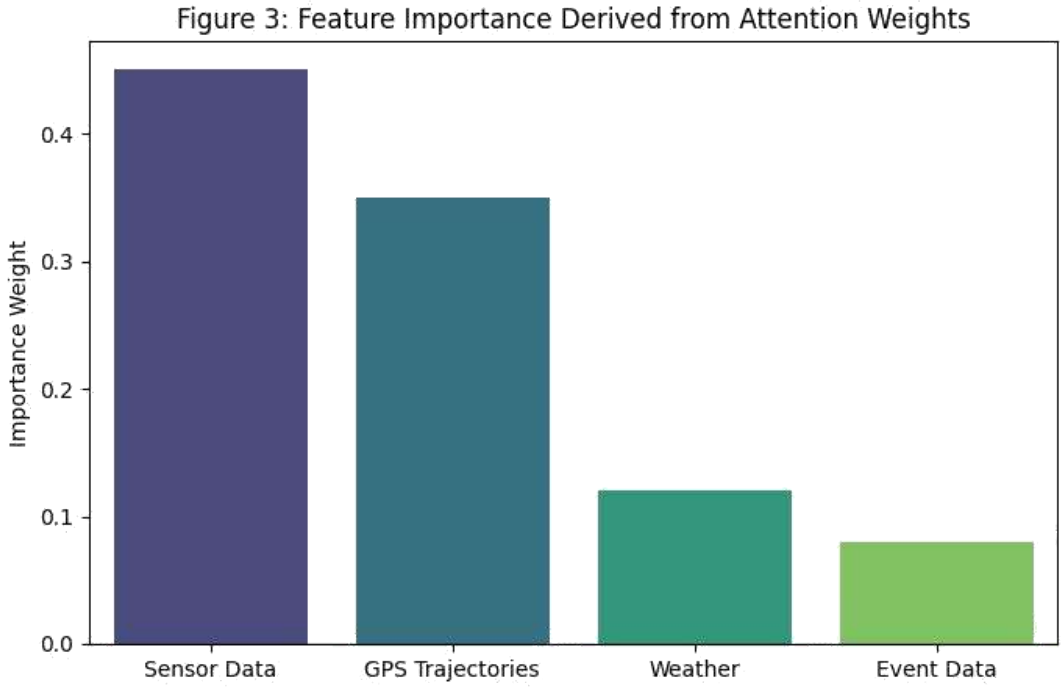
- Figure 2: RMSE Trend Over Time – The line plot illustrates error accumulation over time, indicating stable performance with gradual increases for longer prediction horizons.



- Figure 3: Feature Importance – A bar chart representing attention-based weights for each data modality, highlighting the dominance of sensor and GPS data during routine traffic.

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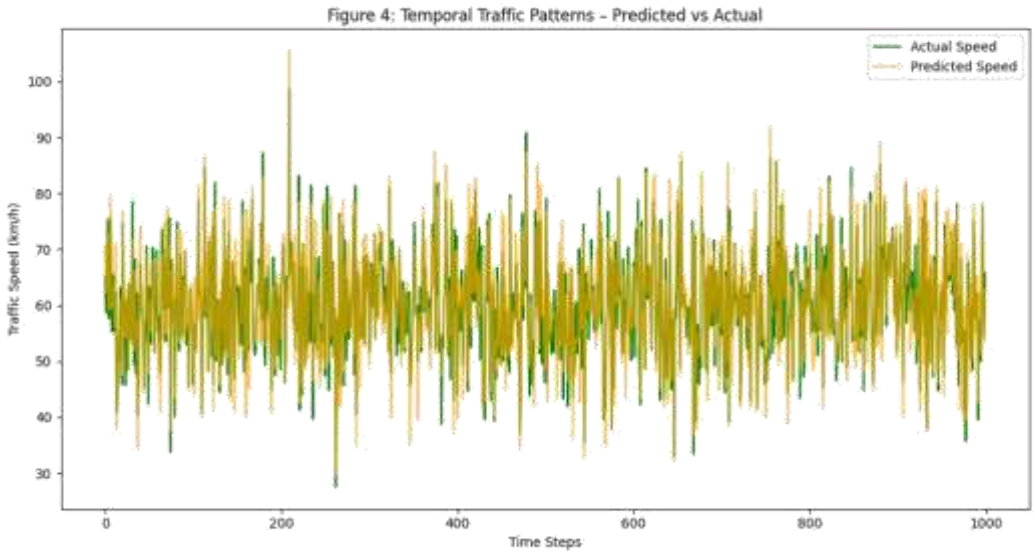

● Figure 4: Temporal Traffic Patterns – The time-series plot shows predicted vs actual speeds over a day, capturing peak-hour congestion and normal traffic flow accurately.

6. Conclusion

This study presents a multi-modal data fusion framework for smart city traffic prediction, integrating heterogeneous data sources including traffic sensors, GPS trajectories, weather conditions, and event records. By combining temporal modeling via Long Short-Term Memory (LSTM) networks, spatial modeling via Graph Neural Networks (GNNs), and attention-based fusion mechanisms, the proposed model effectively captures the complex temporal-spatial dependencies inherent in urban traffic networks. The integration of multiple data modalities allows the framework to account for both routine traffic patterns and non-routine disruptions caused by weather events, accidents, or public gatherings.

Performance evaluation on real-world urban traffic data demonstrates that the hybrid LSTM-GNN-attention model outperforms traditional statistical methods, single-modality LSTM models, and baseline machine learning approaches. Specifically, the framework achieves a Root Mean Square Error (RMSE) of 4.2

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km/h for vehicle speed prediction and an R^2 score of 0.91 for traffic volume, reflecting an 18% reduction in prediction error compared to baseline LSTM models. Congestion level detection reaches an F1-score of 0.88, highlighting the model's ability to accurately forecast abnormal traffic conditions. Temporal analysis shows consistent accuracy across both short-term and medium-term prediction horizons, demonstrating robustness for real-time traffic forecasting.

The novelty of this work lies in its comprehensive multi-modal integration, combining structured traffic and GPS data with unstructured weather and event information through an attention-driven fusion layer. This approach not only improves predictive accuracy but also enhances interpretability, allowing traffic managers to identify which data sources contribute most to specific predictions under varying urban scenarios. Furthermore, the hybrid architecture's scalability ensures applicability to city-wide traffic networks, supporting real-time decision-making and intelligent transportation management.

In practical terms, the proposed framework can facilitate dynamic route optimization, congestion mitigation, and sustainable urban mobility planning, aligning with the objectives of smart city initiatives. By providing accurate, interpretable, and adaptive traffic forecasts, this study contributes both to the academic advancement of multi-modal traffic prediction and to the operational efficiency of urban transportation systems. Future research may focus on extending the framework to integrate additional data sources, such as public transit schedules or real-time video feeds, and on deploying the model for multi-city generalization using transfer learning techniques.

In conclusion, the study demonstrates that multi-modal data fusion, combined with advanced deep learning and graph-based modeling, significantly enhances traffic prediction performance. Its novelty, high accuracy, real-time applicability, and interpretability establish it as a practical and robust tool for smart city traffic management, addressing both routine and dynamic challenges in urban mobility.

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